Impact of Image Augmentation in COVID-19 Detection Using Chest X-Ray Images

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***Abstract*—COVID-19 continues to have a devastating impact on people's lives worldwide. In order to combat this condition, it is critical to test affected people in a timely and cost-effective manner. Radiological examination is one of the most efficient ways to attain this goal, with the most widely available and least expensive alternative being a CXR. The artificial intelligence and data science communities have aided in the global response to COVID-19, a novel coronavirus. Detection and diagnosis techniques have focused on developing rapid diagnostic approaches based on chest X-rays and deep learning. In this paper, we have analyzed the impact of augmentation in COVID-19 CXR images with normal lung opacity and viral pneumonia images and presented a model for the detection of COVID-19.**

***Keywords*—Augmentation, Convolution Neural Network, Deep Learning, Lung Opacity, Radiography**

I. Introduction

According to WHO in Wuhan, China's largest urban area, the first official case of Coronavirus was recorded. The rapid spread of Covid-19 is the biggest problem facing humanity today. The number of persons who have deceased as a result of Covid-19 over the world has surpassed five million, according to the Johns Hopkins University (JHU) Coronavirus Resource Center, and It has been classified as a global pandemic by the World Health Organization (WHO) [1]. An epidemic that becomes a pandemic has a disastrous impact on worldwide health and well-being. The situation is termed coronavirus disease 2019, and it is caused by the same Coronavirus that causes SARS (SARS-CoV). This Coronavirus is related to SARS and MERS. However, it is more deadly and aggressive than those viruses (2019-nCoV). This infectious disease spreads quicker than the ordinary flu virus (through respiratory droplet infection). As a result, COVID-19 positive cases must be identified as soon as possible to prevent the virus from spreading further.

COVID-19 is now identified using reverse transcription-polymerase chain reaction (RT-PCR) genetic testing. These tests are exact and possible to detect and analyze the virus even if a trace of it is present in the patient sample. It is worth emphasizing, the PCR test, on the other hand, is highly complicated, time-consuming, and costly. As a result, not every medical facility is equipped to handle it. Because of these drawbacks, radiography scanning can be used as a stand-in for other methods of illness detection. The existence of the new Coronavirus and its symptoms can be detected using chest radiography images. Viruses in this family, according to research, appear in radiography images in a significant way. As a result, radiographic image categorization, such as a chest X-ray, can be more accurate and faster and less expensive than a PCR test. Chest X-rays are also less expensive than other radiological examinations, such as CT scans, and may be obtained at almost any clinic.

The only drawback to using chest X-rays to discover COVID-19 patients is that skilled specialists are not always available, particularly in remote areas. Furthermore, because many clinicians have never seen COVID-19 positive patient Chest X-rays, the radiological symptoms associated with COVID-19 are novel and surprising. As a result, we suggested a simple and less expensive deep learning-based technique for categorizing Covid-19 positive and negative cases using X-ray scans of the chest.

II. Literature Survey

Medical diagnosis has made extensive use of computer vision. It is beneficial in medical specialities that need visual examinations, such as dermatology. Computer vision is used to detect whether a skin abnormality is an early indicator of skin cancer. It has also been shown to work well in procedures and treatments. Medical imaging such as CT scans, MRIs, PET scans, ultrasounds, and CXR pictures are used in computer vision systems. Various research concentrated on medical images to aid in examining if there are any viruses in the lungs. Most of the research used deep learning-based algorithms to identify pneumonia, various thoracic illnesses, skin cancer, haemorrhage categorization, and other medical images. Despite their modest design, some of these programmes have yielded promising effects. Cohen et al. [3] presented a neural network model for forecasting and evaluating pneumonia severity in general and COVID-19 CXR images for escalation and de-escalation of care in the critical care unit as tracking medication success. Asmaa Abbas et al. [4] developed a deep neural network for identifying chest x-rays using DeTracC (Decompose, Transfer, and Compose).

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Amit Kumar Das et al.[10] In their suggested work, they used various state-of-the-art models such as DenseNet201, Resnet50V2, and Inceptionv3. To make the forecasts, they trained all of the models independently. They were 91.62 per cent accurate in their classification. They also created a public-use application. F. Y. Santoso et al.[11] based on the Xception paradigm, developed a modified deep neural network. This model is made up of two dense layer stacks and a batch normalization layer. They included these layers to avoid the model being too compact. Their proposed model outperforms Resnet50, InceptionV3, and Xception in performance. However, they take longer to compute than Resnet50, InceptionV3, and Xception. B. K. Umri et al.[12] used Adaptive Histogram to acquire detection results, the dataset is evaluated using two scenarios using the Contrast Limited Adaptive Histogram Equalization (CLAHE) and Convolutional Neural Networks (CNN) approaches. Their research revealed that the application of CLAHE affects the accuracy of CNN and their models showed better results than VGG16 transfer learning.

S. Tang et al.[13] presented a deep learning ensemble covid model, which is generated by taking the number of snapshots of the COVID-Net model, which is credited with being the first to develop a COVID-19 case identification approach that is open-source. Their model had a 95 per cent accuracy rate, higher than the COVID-Net model's 93.3 per cent. P. Dutta et al.[14] proposed multilayer CNN with a transfer learning model. They have done their research based on chest CT (Computed Tomography) images. It extracts features using convolution and pooling, just like CNN. The weights of the dataset Imagenet are included in their transfer learning model. R. Bhadra et al.[15] proposed a multilayer CNN architecture. They have performed the blind testing and the ten fold cross-validation method on their proposed approach and achieved an accuracy of 99.1%.

III. Dataset

A dataset of CXR images for positive instances of COVID-19 and Normal and Viral Pneumonia images was created by a team of scholars from Qatar University and the University of Dhaka, as well as Pakistani and Bangladeshi partners, in collaboration with medical specialists. This COVID data is gathered from various publicly available datasets, online sources, and peer-reviewed studies. The padchest dataset yielded 2473 CXR pictures, 183 CXR photos from a medical school in Germany. SIRM, Github, Kaggle, and Tweeter contributed 559 CXR images. Another Github source provided 400 CXR pictures.[7]. TABLE I shows the dataset statistics, and Figure 1 depicts some of the dataset's sample photos.

TABLE I
DATASET STATISTICS

Healthy Samples	10192
Lung Opacity samples	6012
Viral Pneumonia samples	1345
COVID-19 samples	3616

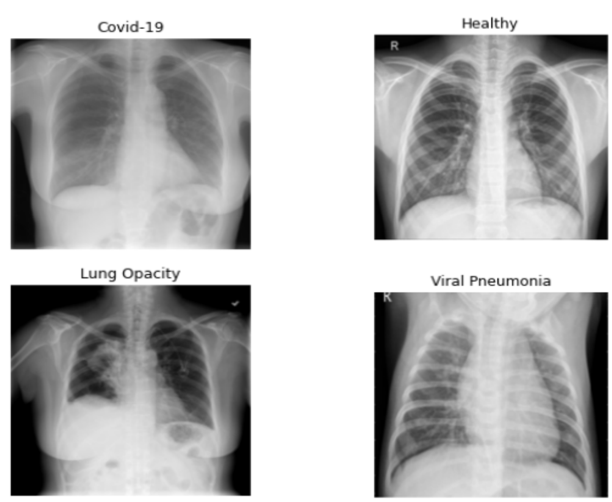

Fig. 1. Sample Images from Radiography Database

IV. Methodology

This section describes the model which includes the phases used for covid-19 detection. The phases are shown in Fig.2. We looked at images of normal, COVID-19, lung opacity, and

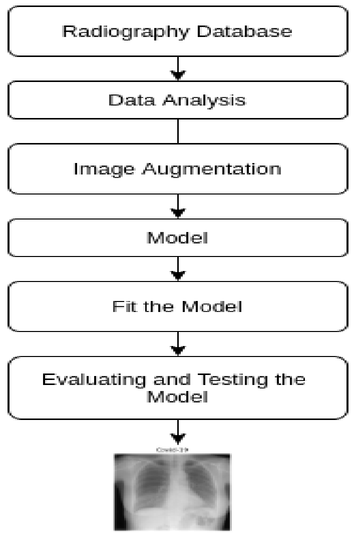

Fig. 2. Proposed Methodology

viral pneumonia during the data analysis phase. Section V explores this. Image augmentation is a technique for modifying original photographs by applying numerous transformations to them, resulting in a large number of different versions of the same image. For picture transformation, we utilized Keras ImageDataGenerator. The ImageDataGenerator class in Keras allows us to rapidly and easily supplement photos. Standardization, rotation, shifts, flips, brightness alterations, and more are among the enhancement choices available. we have used parameters rotation_range=20, width_shift_range=0.2, height_shift_range=0.2 . Designed our model, which consists of eight blocks. In the first block, we have a convolution layer with 32 kernels of size 3*3, followed by a batch normalization layer. In the last block, we do not have a convolutional layer, and there we have a flattened layer, batch normalization layer, dense layer, activation layer with RELU activation function and dropout layer. We have a convolution layer with 64 3*3 kernels, apart from the first and last block.

Alternatively, we have convolution and batch normalisation layers in three blocks. In the other four blocks, we have convolution, batch normalisation, average pooling, and dropout layers. The dropout layer has a value of 0.25, and we have used ReLU as an activation function. The next phase is to fit the model. We have compiled the model using Adam optimizer, categorical/crossentropy as loss and recall as metrics. The last phase evaluates the model and predicts the results.

V. Observation and Results

A. Data Analysis

In this phase, we have calculated the mean and standard deviation of images concerning each class. Also, we can see from scatter plot Fig.10 COVID-19 samples tend to have slightly higher mean and standard deviation than other samples of lung opacity, normal and viral pneumonia. In Fig.4, we can see that viral pneumonia, lung opacity and normal lungs look slightly larger than average COVID-19 lungs. After performing image augmentation we have found.

- To prepare a model There are 16933 photos in 4 classifications..
- To put the model to the test There are 4232 photos in all, divided into four categories.

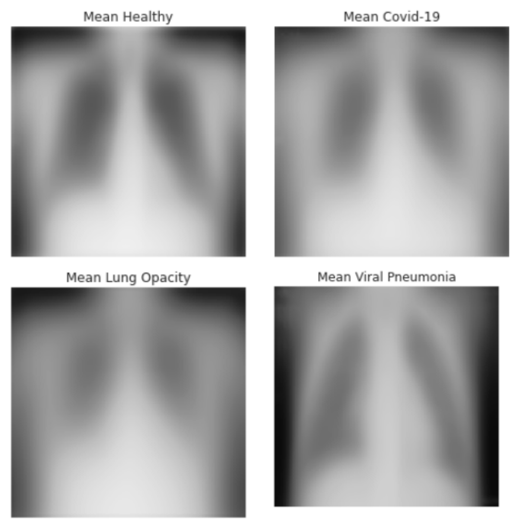

Fig. 3. Average of mean of sample images

B. Training and Performance Plots

In Fig.4, we can observe that as the number of epochs grows, the pace of learning drops which is suitable for the model. In Fig.5, training and validation loss has been shown. In training and validation, the loss is approximately equal to 1.

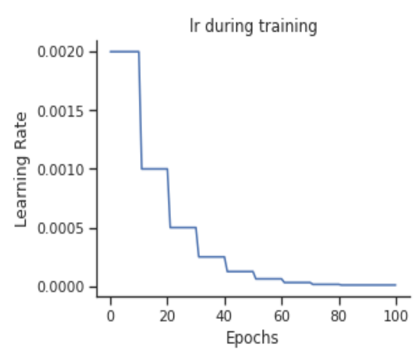

Fig. 4. Learning rate plot

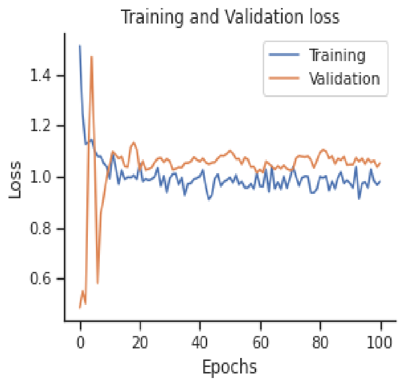

Fig. 5. Training and Validation Loss Plot

C. Results on Test Dataset

Fig.6 shows the confusion matrix for the test dataset. We can compare actual and expected values using the confusion matrix. The confusion matrix is a N x N matrix with N indicating the number of classes.

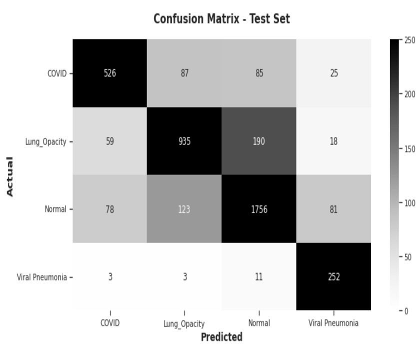

Fig. 6. Confusion Matrix

Precision measures a machine learning model's performance – the accuracy of a model's optimistic prediction—the total number of true positives + false positives divided by the total number of genuine positives. Figure.7 precision is shown for each class, and the total precision is 78.4%.

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

How many true positives were recalled (discovered), i.e. how many right hits were also found, is referred to as recall.? In Fig.8, recall is shown for each class.

$$\text{Recall} = \frac{TP}{(TP + FN)}$$

The F-score is a metric that considers both recall and precision. It is defined as follows:

$$\text{F-Score} = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

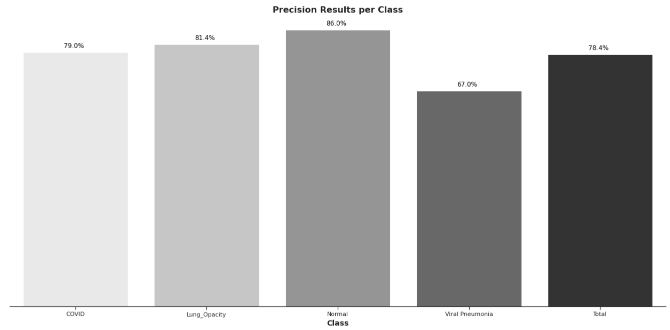

Fig. 7. Precision Plot

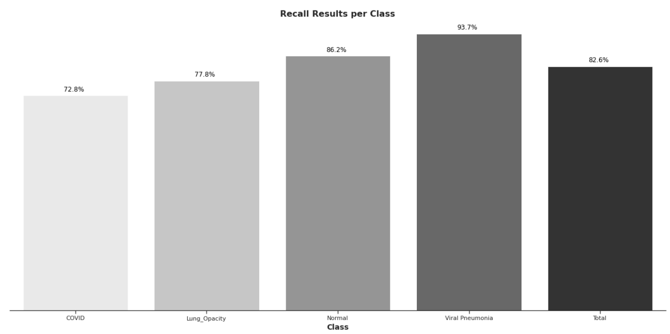

Fig. 8. Recall Plot

In Fig.9 F-Score is shown for each class and total f-score is 79.9% .

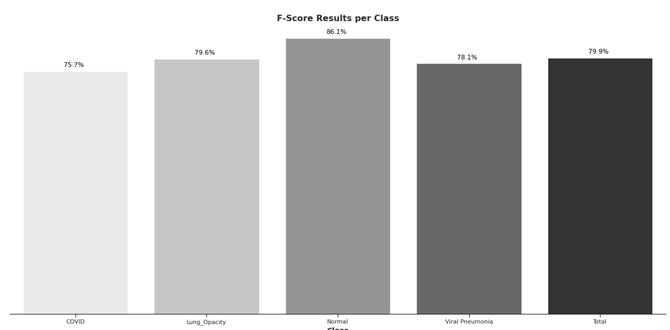

Fig. 9. F-Score Plot

1) Overall Results: Table II shows the overall results on with augmentation and without augmentation. After performing image augmentation model showing better results as compared to without augmentation.

TABLE II
RESULTS ON TEST DATA

	With Augmentation	Without Augmentation
Precision	78.36%	62.32%
Recall	82.60%	71.08%
F-Score	79.88%	62.61%
Accuracy	81.97%	66.38%

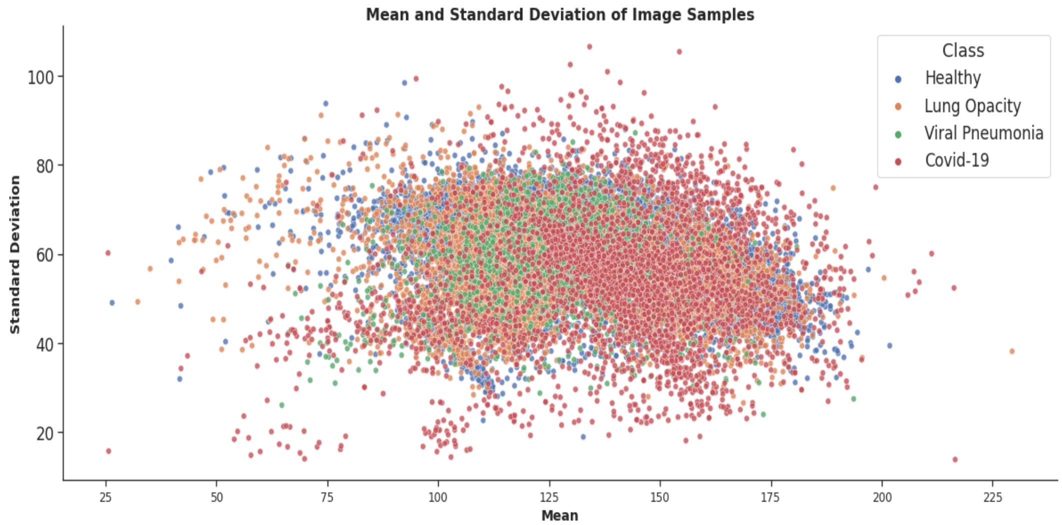

Fig. 10. Image Samples Mean and Standard Deviation

VI. Conclusion and Future Work

Millions of people have died because of the new COVID-19 virus, particularly the elderly and health problems. After collecting a proper respiratory tract specimen, the reverse-transcription polymerase chain reaction (RT-PCR) test is the standard approach for detecting and diagnosing COVID-19. However, it is time-consuming and expensive in many cases, necessitating the development of novel low-cost, quick diagnostic methods to aid clinical assessment. VGG-16 inspired our methodology for COVID-19 detection utilising radiography pictures, which we demonstrated. Our overall model accuracy for the radiography database is 81.97%. The production of high-quality datasets should be a top priority because the more datasets available, the better our neural network models will perform. We will increase the accuracy of our model in future studies.

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